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Implicit attentional biases in a changing environment

Benchi Wang[a,b,*], Jan Theeuwes[c,d]

[a] Institute for Brain Research and Rehabilitation, South China Normal University, China
[b] Key Laboratory of Brain, Cognition and Education Sciences (South China Normal University), Ministry of Education, China
[c] Department of Experimental and Applied Psychology, Vrije Universiteit Amsterdam, Amsterdam, the Netherlands
[d] Institute Brain and Behavior Amsterdam (iBBA), the Netherlands

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ABSTRACT

The current study investigates whether statistical regularities that change over time affect attentional selection. While searching for a target singleton, the distractor singleton was presented much more often in one location than in all other locations. Crucially, the location that had a distractor much more often, changed to new locations during the course of the experiment. Here we established exactly how the bias of attention followed these changes in the display. Unlike previous studies, we show that selection was remarkably flexible as the attentional bias followed the changes in the environment incorporating contributions of previous contingencies to the current attentional bias. Importantly, the initial learning experience had a lingering and enduring effect on subsequent attentional biases. We argue that the weights within the spatial priority map of selection are adjusted to changing environments, even though observers are unaware of these changes in the environment.

1. Introduction

Humans have the ability to detect, extract and use regularities in the environment to guide behavior. What we have experienced in the past, will drive our current actions. Even though this general mechanism (referred to as statistical learning) has been recognized in many domains of cognitive science such as motor learning, language acquisition, and conditioning (e.g., Frost, Armstrong, Siegelman, & Christiansen, 2015), there has been a large interest in its role in attentional selection (Awh, Belopolsky, & Theeuwes, 2012; Theeuwes, 2018, 2019). Previous studies mainly focused on trial-to-trial target priming effects showing that the selection of a target becomes more efficient when its features are primed during the previous trial (e.g., Hickey, Chelazzi, & Theeuwes, 2010; Maljkovic & Nakayama, 1994); Recently there have been several studies that elaborated spatial- and feature-based history effects over longer time scales showing that attentional selection is driven by history effect above and beyond the classic voluntary, top-down and stimulus-driven, bottom-up effects (Failing, Feldmann-Wüstefeld, Wang, Olivers, & Theeuwes, 2019; Failing, Wang, & Theeuwes, 2019; Ferrante et al., 2018; Goschy, Bakos, Müller, & Zehetleitner, 2014; Stilwell, Bahle, & Vecera, 2019; Wang & Theeuwes, 2018a, 2018b, 2018c; for reviews, see Failing & Theeuwes, 2018; Theeuwes, 2018).

One of the most fundamental capacities of any organism is the ability to extract the distributional properties of sensory input across time and space. Through statistical learning (SL) we are capable of extracting repeated patterns and regularities from the environment (Goujon, Didierjean, & Thorpe, 2015). Studies investigating visual statistical learning (VSL) have demonstrated that people can learn relationships among visual objects. Following the classic work on syllable learning (Saffran, Aslin, & Newport, 1996), studies have used sequentially presented shapes in which subtle probabilistic relationships were introduced (Fiser & Aslin, 2002; Turk-Browne, Jungé, & Scholl, 2005). For example, in Fiser & Aslin, 2002, participants were exposed to a continuous stream of non-sense shapes, in which particular triplets (three shapes presented in a sequence) could appear. Later during surprise recall, participants showed greater familiarity with the triplets than with foil triplets, indicating that they learned higher transitional probabilities between the shapes. Since VSL was observed when stimuli were viewed passively without an explicit task (Fiser & Aslin, 2001) and when observers were performing a completely different unrelated task (Saffran, Newport, Aslin, Tunick, & Barrueco, 1997), it was argued that the mere exposure to these streams was enough to learn these regularities (e.g., Fiser & Aslin, 2002).

There is also evidence that learning statistical regularities can bias attentional visual selection. The most prominent research in this domain is known as "contextual cueing". This type of research showed that searching for a target is facilitated when it appears in a visual lay-

* Corresponding author at: Institute for Brain Research and Rehabilitation, South China Normal University, China.
E-mail address: wangbenchi.swift@gmail.com (B. Wang).
URL: https://github.com/wangbenchi/Shared_data (B. Wang).

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out that was previously searched relative to visual lay-outs that were never seen before (Chun & Jiang, 1998, 1999; Jiang & Chun, 2001). In the typical contextual cueing paradigm, participants searched for a target 'T' among distractors 'L's in sparsely scattered configurations. During the experiment, half of the display configurations were repeated across blocks while others were only seen once. The classic finding is that participants are faster in finding targets when they appeared in repeated configurations (particular displays consisting of a target presented among distractors), suggesting that participants have learned to associate the location of the target with a particular spatial configuration involving the target and its surrounding distractors. It is well known that visual search is improved when participants knew the likely location of the target. Indeed, the classic Posner studies from the 1980s (Posner, 1980) showed that people are faster to detect targets appearing in probable locations than improbable locations (Shaw & Shaw, 1977). Notably however, unlike what is found in these classic cueing studies, in contextual cueing, the effect occurs without instruction, and without intention to learn. Moreover, observers often cannot report which configurations they had seen before, suggesting little awareness for what they had learned (Chun & Jiang, 2003). Contextual cueing studies hence reveal that the visual system is sensitive to regularities in the environment, and that it will encode and retrieve information that is relevant for the task.

The contextual cueing studies (and VSL experiments in general) have provided important insights regarding how learning occurs for attended and task-relevant properties such as searching for a specific target among its distractors (Chun & Jiang, 1998), or selectively attending sequentially presented target shapes (Turk-Browne et al., 2005). However, recently, in a series of experiments Wang and Theeuwes (2018a, 2018b, 2018c) provided evidence that the effect of VSL on visual attention is much more ubiquitous than previously assumed. Wang and Theeuwes showed that people are not only able to learn the statistical regularities of the object they are looking for (i.e., the target) but also learn the regularities concerning objects they need to avoid (i.e., the distractor). In all studies, Wang and Theeuwes (2018a, 2018b, 2018c) used the well-established additional singleton task (Theeuwes, 1991, 1992) and manipulated the distributional properties of the distractor (the distractor's location and its features). They showed that when the distractor appeared more often in one location than in all other locations, its distracting effect (the extent to which it captured attention) was dramatically reduced. Importantly, they demonstrated the existence of a gradient of spatial suppression around this high-probability (distractor) location, suggesting that this location is suppressed and as such competes less for attention than all other locations in the visual field. Also, when the target happened to be presented at that high-probability location, the selection of the target was less efficient and reaction time went up. Critically, the effect is not due to some form of trial-to-trial repetition priming (repetition suppression; Wang & Theeuwes, 2018a; Zhang, Allenmark, Liesefeld, Shi, & Muller, 2019) nor is it the result of some waning of a repeated capture response to that location (habituation; Wang & Theeuwes, 2018b). Also, the probability of the distractor feature (for example, the distractor was in 80% of the trials red and 20% of trial green, with grey background elements; see Wang & Theeuwes, 2018c, Experiments 3 and 4) had no effect on attentional selection, suggesting that this effect is mainly spatial in origin (but see Stilwell et al., 2019).

It is also important to note that the studies of Wang and Theeuwes (2018a, 2018b, 2018c) are about distractor-location probability learning only. Although previous studies have manipulated the target probability (for example, as in studies of Ferrante et al., 2018 and of Zhang et al., 2019), it is important to realize that the effects reported by Wang and Theeuwes (2018a, 2018b, 2018c) are solely about the distractor-location probability. In a recent study (Failing, Wang, et al., 2019), it was explicitly tested whether the joint probability of the target and distractor distribution that was responsible for the attentional suppression of the distractor location or whether the probability of the distractor was the only reason. The results were very clear in showing that the attentional suppression of the distractor location is independent of the effect generated by any regularities regarding the location of the target.

More recently, Wang, Samara, and Theeuwes (2019) showed that also the probability of making a saccadic eye movement to a distractor presented at the high-probability location was reduced relative to when the distractor appeared at a low-probability location, demonstrating a robust effect on the oculomotor system. Importantly, Wang and colleagues (Wang, van Driel, Ort, & Theeuwes, 2019) found that *proactive suppression* is already applied before the search display onset, by showing that there is enhanced power in parieto-occipital alpha oscillations contralateral to the high-probability location. Locked to the display onset, ERP analysis showed a distractor-suppression-related distractor positivity (P_D) component for this location, regardless of whether distracting information is presented at the high-probability location or not. As with previous VSL studies, in all Wang and Theeuwes's studies observers were basically unaware of the regularities. Wang and Theeuwes (Theeuwes, 2019; Wang & Theeuwes, 2018a, 2018b, 2018c) concluded that this type of learning induces plasticity within the spatial priority map, such that the location containing distracting information plays a weaker role in the attentional biased competition within the priority map (Ferrante et al., 2018).

The earlier discussed Wang and Theeuwes (2018a, 2018b, 2018c) studies investigated regularities regarding the distractor location. There are also many studies that manipulated the regularities regarding the location of the target (Ferrante et al., 2018; Zhang et al., 2019). All these studies basically show that a target presented at a more likely position is detected faster than when presented at a rare location. Regularities regarding the target (leading to enhancement) and regularities regarding the distractor (leading to suppression) all affect the weights within the spatial priority map ultimately determine the selection biases (Ferrante et al., 2018; Gaspelin & Luck, 2018; Theeuwes, 2019).

Typically, in the type of experiments outlined above, the spatial regularities introduced remain constant. It is however important to determine how flexible the allocation of attention is in a changing environment. From studies investigating the effect of reward on attentional selection have shown that attentional biases persist even when the reward is no longer given. For example, Della Libera and Chelazzi (2009) showed that, when during training the selection of stimuli was rewarded, these stimuli continued to affect selection during a test session even when the selection of these was not beneficial anymore (see also Anderson, Laurent, & Yantis, 2011; Failing & Theeuwes, 2015). These studies show that if contingencies are no longer in place, at least for some trials selection biases remain the way they were trained. The question we addressed here was not whether biases remain when a contingency is no longer in place but instead how these biases change when a contingency changes unpredictably during the experiment. In other words, do people adapt to regularities when they change over time. From an evolutionary view, it would be highly beneficial if selection priorities would quickly adapt to a dynamically changing environment. It is not immediately clear whether attentional selection adapts to a changing environment. On the one hand, it is likely that there is little, if any, adaptation to changing regularities because in Wang and Theeuwes's (2018a) studies participants had no explicit knowledge about the regularities presented in the display. It is generally agreed that implicit knowledge tends to be relatively inflexible, and bound to the surface features of to-be-learned material (Cleeremans, Destrebecqz, & Boyer, 1998; Tulving & Schacter, 1990). This is consistent with other research investigating attentional selection when regularities in the environment change. In one of those studies (Jiang, Swallow, Rosenbaum, & Herzig, 2013), participants searched for a target that was more likely to appear in one quadrant of the display than in all other quadrants. Not surprising, participants learned this contingency an effect which was labeled as "target location probability cueing" (see Geng & Behrmann, 2005 for this term). Crucial for the present discussion, however, when the target no longer appeared more often in one of the quadrant, but instead was presented equally often in all quadrants, the attentional bias persisted suggesting little adaptation to a changing environment (see also Chun & Jiang, 1998; Makovski & Jiang, 2010; Manginelli & Pollmann, 2009).

Sauter, Liesefeld, and Müller (2019) also examined whether learned regularities are updated when the environment changes. In this study participants searched for a grey tilted target line among 34 grey vertical non-target lines. A distractor could be a red vertical or horizontal bar, that is salient and known to capture attention. The results showed that the interference was reduced for distractors presented in frequent regions in the display (where the distractor often appeared) than when it was presented in rare locations. This effect labeled 'distractor location probability cueing' (see Goschy et al., 2014) indicates that participants are able to learn where distractors are likely to be presented and this in turn reduced the amount of interference, very similar to findings in Wang and Theeuwes (2018a, 2018b, 2018c). Critically however this study showed that this effect persisted over a 24 h break and more importantly, took several hundred trials to get unlearned when the distribution of where the distractor could appear was changed to even (50%: 50%). This study is a clear demonstration of that the attentional bias is not flexible and only changes after many trials of unlearning.

The overall view from these studies is that, through associative learning, highly specific associations are formed, which cannot easily be changed (e.g., Chun & Jiang, 1998; Zellin, von Mühlenen, Müller, & Conci, 2014). In another example, Zellin et al., 2014 showed that people quickly learn (i.e., after just three repetitions) particular context-target associations. However, when those particular associations were changed (i.e., the target was presented at another location within a particular context) learning was extremely slow and effortful requiring 3 days of training with up to 80 repetitions. The general claim is that the initial learning of statistical regularities causes proactive interference of learning new statistical regularities (Lustig & Hasher, 2001). Because of the initial exposure to particular regularities, attention is being blocked from being reallocated to new regularities. Similar findings are found in studies employing auditory statistical learning. In those studies it was shown that the successful extraction of the structure in an auditory statistical learning reduced the ability to learn a subsequent structure (e.g., Gebhart, Newport, & Aslin, 2009). If, however the exposure to the second structure was very long, some new learning was found.

Alternatively, it is possible that the type of VSL that we study here is highly flexible, possibly even because it is implicit. It is then assumed that the statistical probabilities are constantly and implicitly weighted, and selection is adapted accordingly. Also, it is feasible that learning is in fact very flexible because in the Wang & Theeuwes paradigm, regularities are introduced regarding the location of the distractor and not of the target as in all their previous studies. Because it is about statistical learning of objects that are not part of the task set (i.e., distractors), learning may turn out to be very flexible. If learning would be flexible, the question arises if and in what way the previous learning experience (i.e., lingering biases) have an effect on attentional selection.

The present study quantified how attentional biases towards the distractor developed over time in a changing environment by incorporating the contributions of previous regularities to the current attentional bias. By means of best fitting Gaussian function we established exactly how attention was biased over time and space.

2. Experiment 1

2.1. Method

Twenty-four naïve adults (5 females, mean age = 19.9 years, SD = 1.01) from Zhejiang Normal University in China participated.[1] Sample size was predetermined based on the main effect of distractor condition (high-probability location, low-probability location, and no-distractor) in Wang and Theeuwes (2018a), *partial* η^2 = 0.85. With 24 subjects and alpha = 0.001, power for the critical effect would be $>$0.99. Participants all reported normal color vision and normal or corrected-to-normal visual acuity. The study was approved by both the Ethical Review Committee of the Vrije Universiteit Amsterdam and the Ethical Review Committee of Zhejiang Normal University.

2.1.1. Stimuli, procedure and design

The display consisted of eight discrete elements with different shapes (one circle vs. seven unfilled diamonds, or vice versa), with each contained a vertical or horizontal grey line (0.15° × 1°; 24 cd/m^2) inside, see Fig. 1. The stimuli were presented on an imaginary circle with a radius of 4°, centered around fixation (a white cross measuring 1° × 1°; 110 cd/m^2), against a black background (7 cd/m^2). The circle's radius was 1°, the other unfilled diamonds were subtended 2° × 2°, and each had a red (35 cd/m^2) or green (60 cd/m^2) outline.

A fixation cross which remained visible throughout a trial. After 500 ms, the search array was presented for 3000 ms or until response. Participants were required to search for a circle (target) among seven diamonds (distractors) or vice versa, and to indicate whether the line segment inside the target was vertical or horizontal, by pressing the 'up' or 'left' key respectively as fast as possible. The inter-trial interval (ITI) was randomly chosen from 500 to 750 ms.

Each trial contained a target which could be a circle or a diamond with equal probability. A uniquely colored distractor singleton was present in 66.6% of trials (*distractor singleton present* condition), which had the same shape as other distractors but had a different color (red or green with an equal probability). In the remaining trials there was no distractor (*distractor singleton absent* condition). All conditions were randomized within blocks. The distractor singleton could appear at eight locations; yet, in each block, one of these distractor locations had a high proportion of 65% (high-probability location); and other 7 locations equally shared a low proportion of 35% (low-probability location). When the distractor was present, the target was equally likely to appear at any low-probability location.[2] In the no-distractor condition, the target was equally likely to appear at any location. Participants were not informed about the probability manipulations.

After 40 practice trials, 10 blocks each containing 120 trials were tested (with a break in between). For each block, there were 52 high-probability location trials and 28 low-probability location trials, and 40 no-distractor trials. In the first 2 blocks, the high-probability location was the same location, but was different across participants. Importantly, to explore how statistical regularities over time and space would impact selection, the high-probability location was moved clockwise to the fourth location away from the previous one (see Fig. 1) after the first 2 blocks (2 times 120 trials) and was kept constant for next 4 blocks (4 times 120 trials). Following these 4 blocks the high-probability location was moved again clockwise to a location three steps away from the current one and was kept constant again for next 4 blocks. We labeled the first high-probability location as *regularity one*, the second one as *regularity two*, and the third one as *regularity three*.

[1] The fact that we have few women in our sample is merely coincidental. Also, there is no evidence that the effects that we study are depend on gender.

[2] The design, that the target never appears at the high-probability location in the distractor present condition, was adopted because we used the exactly same design as in Wang and Theeuwes (2018a). Thus, one might question that the effects reported are due to the target probability and not due to the distractor probability. However, importantly in a recent study, we showed that the probability of the target does not matter: the suppression effect observed here and in previous studies (Wang & Theeuwes, 2018a, 2018b, 2018c) was solely due to the distractor being presented more often in one location (Failing, Wang et al., 2019).

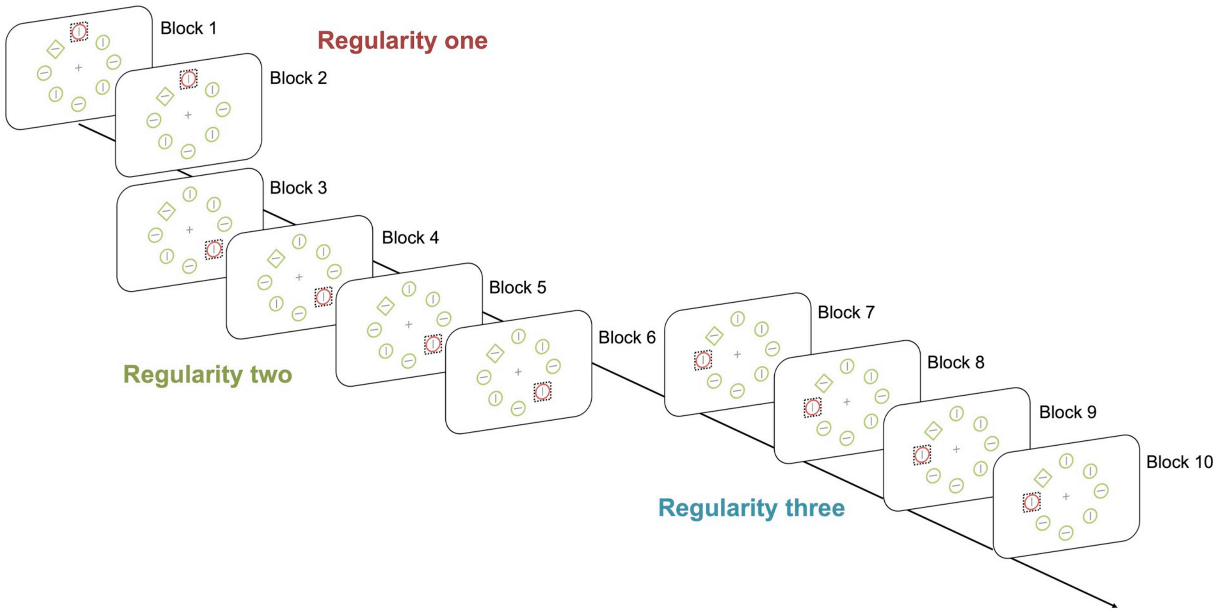

Fig. 1. Examples of the search displays for different regularities, with the dashed outline squares indicates different high-probability locations. Displays are used for illustration purposes only.

2.2. Results

Trials (2.7%) on which the response times (RTs) were larger or smaller than 2.5 standard deviations from the average response time per block per participant were excluded from analyses.

2.2.1. Overall evaluation

Mean RTs and mean error rates are presented in Fig. 2. Repeated measures ANOVA on mean RTs with *distractor condition* (high-probability location, low-probability location, and no-distractor) and *current statistical regularity* (one, two, and three) as factors showed main effects for distractor condition, $F(2, 46) = 169.03$, $p < .001$, partial $\eta^2 = 0.88$, and current statistical regularity, $F(2, 46) = 112.6$, $p < .001$, partial $\eta^2 = 0.83$. The interaction between distractor condition and current statistical regularity was also reliable $F(4, 92) = 6.65$, $p < .001$, partial $\eta^2 = 0.22$, suggesting that learning systematically changed over

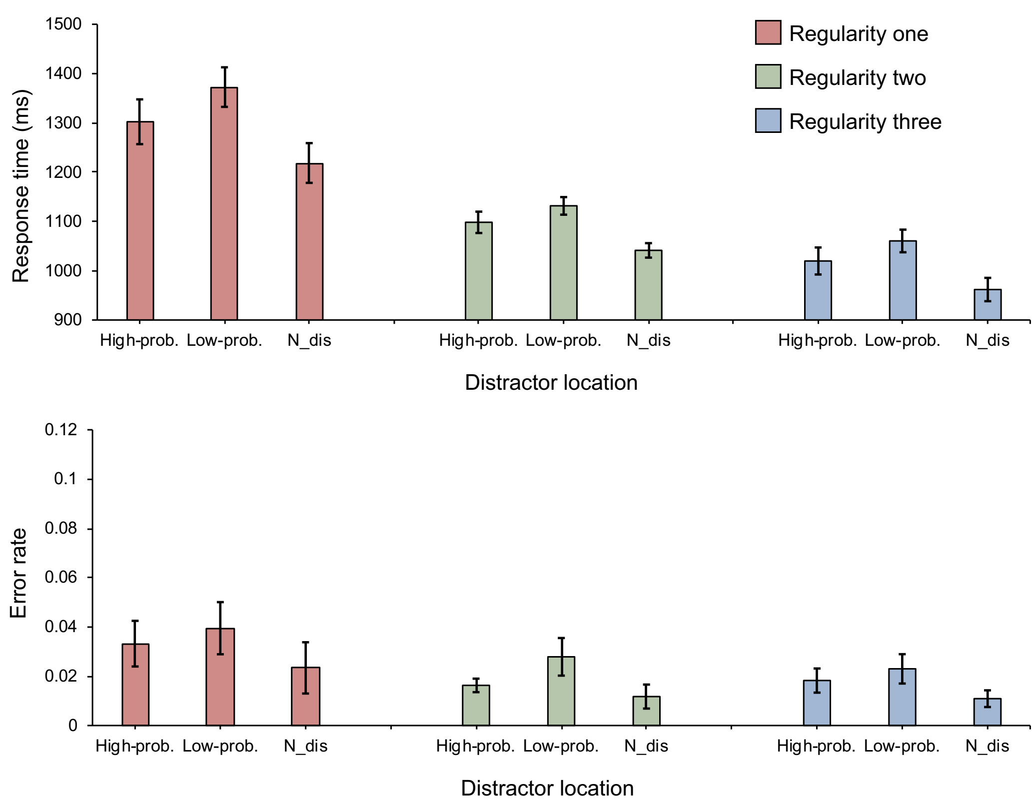

Fig. 2. The mean RTs (upper panel) and the mean error rates (low panel) between different distractor conditions for different regularities. "N_dis" means no-distractor condition. Error bars denote within-subjects 95% confidence intervals (CIs; Morey, 2008).

regularity.

Subsequent planned comparisons showed that compared to the no-distractor condition, there were significant attentional capture effects: for a distractor singleton presented at the high-probability location with all regularities, all $ps < .001$; and for a distractor singleton presented at the low-probability location with all regularities, all $ps < .001$. Crucially, there was also a reliable difference between the high- and low-probability locations for all regularities (one, two, and three), all $ps < .002$, indicating that attentional capture was reduced when the distractor singleton appeared at a high-probability location for each regularity.

The results on error rates partially mimicked those for RTs. Repeated measures ANOVA on mean RTs with *distractor condition* (high-probability location, low-probability location, and no-distractor) and *current statistical regularity* (one, two, and three) as factors showed main effects for distractor condition, $F(2, 46) = 23.65$, $p < .001$, partial $\eta^2 = 0.51$, and current statistical regularity, $F(2, 46) = 9.94$, $p < .001$, partial $\eta^2 = 0.3$. The interaction between distractor condition and current statistical regularity was not reliable, $F < 1$.

2.2.2. No-distractor condition

Mean RTs and mean error rates are presented in Fig. 3. Repeated measures ANOVA on mean RTs with *target position* (high-probability location and low-probability location) and *current statistical regularity* (one, two, and three) as factors showed main effects for target position, $F(1, 23) = 25.56$, $p < .001$, partial $\eta^2 = 0.53$, and current statistical regularity, $F(2, 46) = 83.12$, $p < .001$, partial $\eta^2 = 0.78$. There was no interaction, $F < 1$. Responses were slow when the target appeared at the high-probability location, and the mean RTs decreased with changing the statistical regularities. There was no effect on error rates, all $ps > .27$.

In short, for each regularity, our results basically replicate the findings in Wang and Theeuwes (2018a). The present results indicate that for each regularity, there is less attentional capture for the high- versus the low-probability location. Moreover, for each regularity when the target is presented at the high-probability location its selection is less efficient (higher RT) than when it is presented at the low-probability location. Overall, this pattern of results indicates that participants quickly adapt to the changing regularities in the environment. Indeed, the location that is most likely to contain a distractor is suppressed relative to the other locations and this suppression moves when this high-probability location changes.

Quantifying the suppression changes across different regularities over space.

To quantify how the spatial suppression changed across the different regularities, we first had to remove the overall general practice effect. For this purpose, we adopted what we refer to as the "Normalized Attentional Capture effect" (Norm-AC effect; i.e., mean RTs in distractor present condition minus distractor absent condition divided by the overall mean RTs for each regularity). The reason for choosing the Norm-AC effect to conduct further analysis is that previous studies using the exact same paradigm (Wang & Theeuwes, 2018a, 2018b) demonstrated that the Norm-AC effect did not change over time with extended training (See Supplementary Information [SI] for details).

In the present study, with *display location* (see Fig. 4A, the first data point represents the top location on the display, marked as "Loc-1") and *current statistical regularity* (one, two, and three) as factors, a repeated ANOVA on the Norm-AC effect revealed that there was a significant main effect for current statistical regularity, $F(2, 46) = 6.36$, $p = .004$, $\eta_p^2 = 0.22$; but not for display location, $F(7, 161) = 1.29$, $p = .26$, $\eta_p^2 = 0.05$. There was also a reliable interaction, $F(14, 322) = 2.62$, $p = .001$, $\eta_p^2 = 0.1$. Together, it suggests that the Norm-AC effect

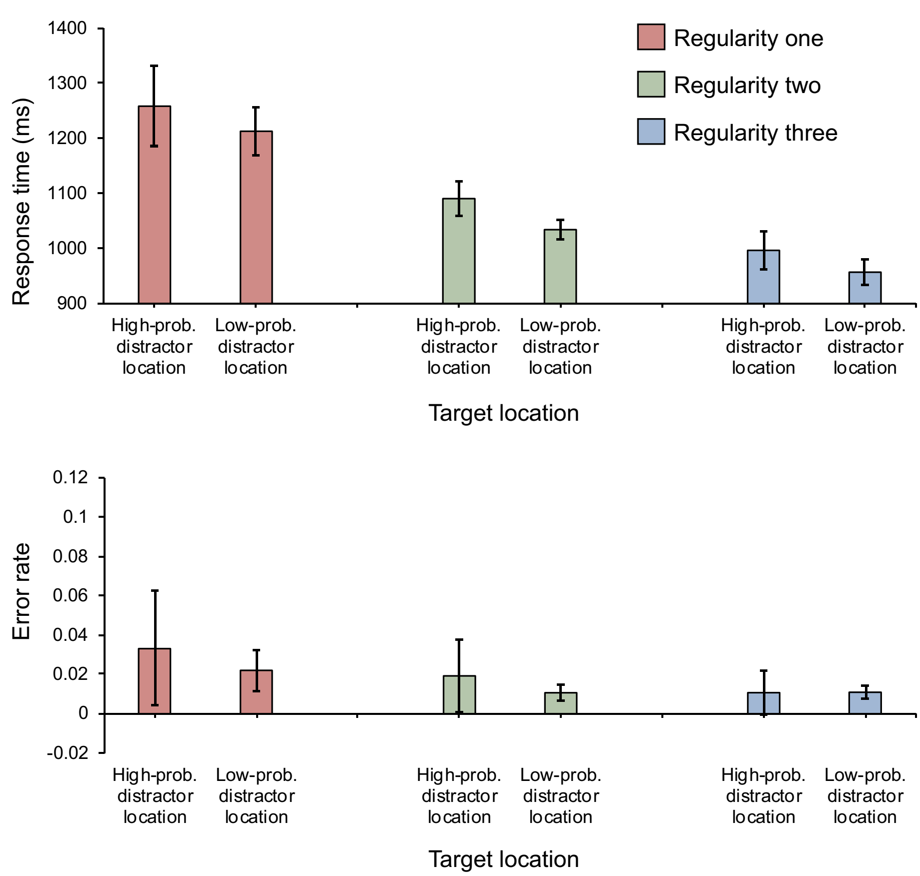

Fig. 3. The mean RTs (upper panel) and the mean error rates (low panel) in the distractor singleton absent condition for different regularities. Error bars denote within-subjects 95% CIs.

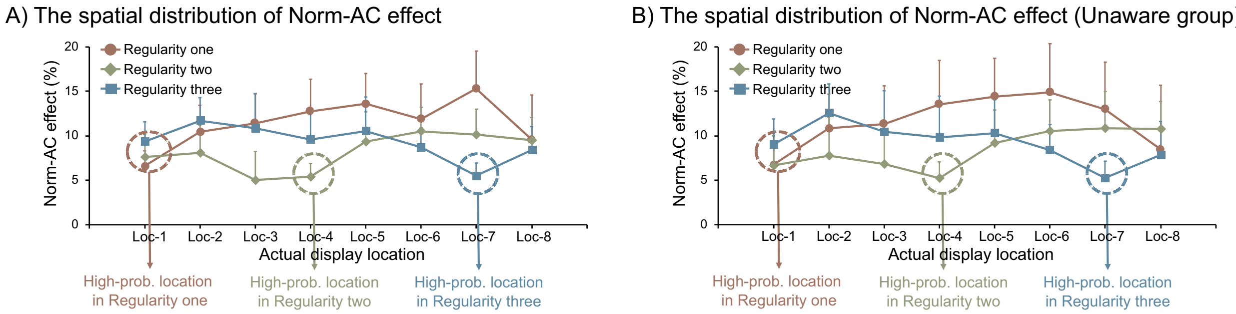

Fig. 4. The spatial gradient of normalized attentional capture effects corresponding to all eight display locations (displayed along the x-axis) in the present study. Error bars denote within-subjects 95% CIs.

systematically changed across different regularities over space.[3]

Furthermore, to explore whether the lingering bias towards the initial high-probability location could be generated without awareness, we excluded nine subjects that indicated correctly any of the high-probability locations after the experiment (see SI for more details about the awareness test) and ran the main analysis again. With *actual display location* and *current statistical regularity* as factors, a repeated ANOVA on Norm-AC effect revealed that there was a significant main effect for current statistical regularity, $F(2, 28) = 3.76$, $p = .036$, $\eta_p^2 = 0.21$; but not for actual display location, $F(7, 98) = 1.38$, $p = .223$, $\eta_p^2 = 0.09$. The interaction was marginally significant, $F(14, 196) = 1.71$, $p = .056$, partial $\eta^2 = 0.11$ (see Fig. 4B). Moreover, when we involved group (aware vs. unaware) as another factor to do the analysis again, we found no interaction with group, all *Fs* < 1.02, all *ps* > .438, suggesting that being aware of the location is not necessary for obtaining the effects, and the learning is basically implicit.

Illustrating the change with Gaussian model fitting.

Previous studies have shown that attention-related phenomenon (e.g., inhibition of return, c.f., Klein, 2000) always generate a spatial gradient which can be qualified with Gaussian model fitting (Bennett & Pratt, 2001; Taylor, Chan, Bennett, & Pratt, 2015; Wang, Yan, Klein, & Wang, 2018). In the present study, we also observed a spatial gradient of the suppression effect (reflected by the Norm-AC effect). Importantly, the observed spatial gradient systematically changed with moving the high-probability location to other locations. To further analyze how it changes, we divided three regularities into five sessions[4] with each including two blocks: *Session one* (*Regularity one*), *Session two and three* (*Regularity two*), and *Session four and five* (*Regularity three*). All locations were aligned to the high-probability locations for different regularities. The farthest location was used twice to make the number of data points the same for both sides of the center. Moreover, the current dataset was modelled by assuming a spatial gradient of the Norm-AC effect as a Gaussian distribution (see Wang et al., 2018 for similar analysis), in which the depth of the Norm-AC effect (*N-AC*) increased as a Gaussian function of the distance (*d*), see below:

$$N - AC = -D \times \exp\left(-\pi \times \left(0.94 \times \frac{d-c}{w}\right)^2\right) + b \tag{1}$$

where *D* is the depth of the best-fitting Gaussian of the spatial gradient of the Norm-AC effect, reflecting the amount of the reduced capture; *c* is the center of the spatial gradient; *w* is the full width at half maximum (FWHM), and *b* is the initial lingering bias (representing the initial attentional capture effect for each regularity/session).

Eq. 1 was fitted to the data separately for different sessions by minimizing the root mean squared (RMS) error between the observed and predicted suppression effects, see Fig. 5A. The best-fitting parameters are shown in Table 1 and Fig. 5B–D. As shown in Fig. 5B, the initial capture effect (i.e., the initial lingering bias; *b*) decreased over sessions, with linear slopes of 0.98% per session, indicating that people continuously picked up the learning effects from previous regularities/sessions. As shown in Fig. 5C, the FWHM of the spatial gradient (*w*) increased first, and then decreased over sessions with a linear slope of 41.9°/session, implying that the reduction of attentional capture effect was extended to all locations, and then its gradient becomes more focused around one location due to lingering biases.

Important changes were observed for the gradient center (*c*). As illustrated in Fig. 5D, it is at the high-probability location in session 1. For sessions 2–3, the center continuously moved towards the new high-probability location but remained biased towards the original high-probability location. However, while the center moved again towards the new high-probability location in sessions 4–5, there was a slight bias in session 4 towards the original high-probability location in session 1, because the original high-probability location still has potential impact. In the final session, the center is close to the new high-probability location.

3. Experiment 2

Even though the high-probability location changed to other locations in the subsequent sessions, the overall probability of containing a distractor at the initial high-probability location was still higher compared to other constant low-probability locations. To make this more explicit: if after 240 trials (the first regularity), the high-probability location switches to another location, at that point and for the following 240 trials, the overall probability of containing a distractor for the first location was higher than for the new high-probability location (regularity two). After 480 trials (240 trials and 240 new location trials) the probabilities of containing a distractor are equal for regularities one and two. However, the probabilities of containing a distractor for regularities one and two are always higher than that for other constant low-probability locations. It is therefore possible that the overall results do not reflect learning of the new contingencies, but rather indicates an overall bias in which simply the overall probabilities across the whole experiment are weighted. Even though feasible, if that were the case, the overall probability for the three different high-probabilities locations should have been the same and the spatial gradient should have been centered around these locations rather than that the later gradient was biased by the previous regularity as we found in Experiment 1. In any case, we still conducted the present experiment to exclude this possibility.

3.1. Method

Twenty-four adults (3 females, mean age = 19.29 years, SD = 0.69) from Zhejiang Normal University in China participated in this experiment. The procedure was similar to Experiment 1 except that in the

[3] We also conducted multiple follow-up comparisons to explain the interaction, see SI for details.

[4] The word "session" was used to describe the aggregate of two blocks, that does not indicate that these sessions were run on different days

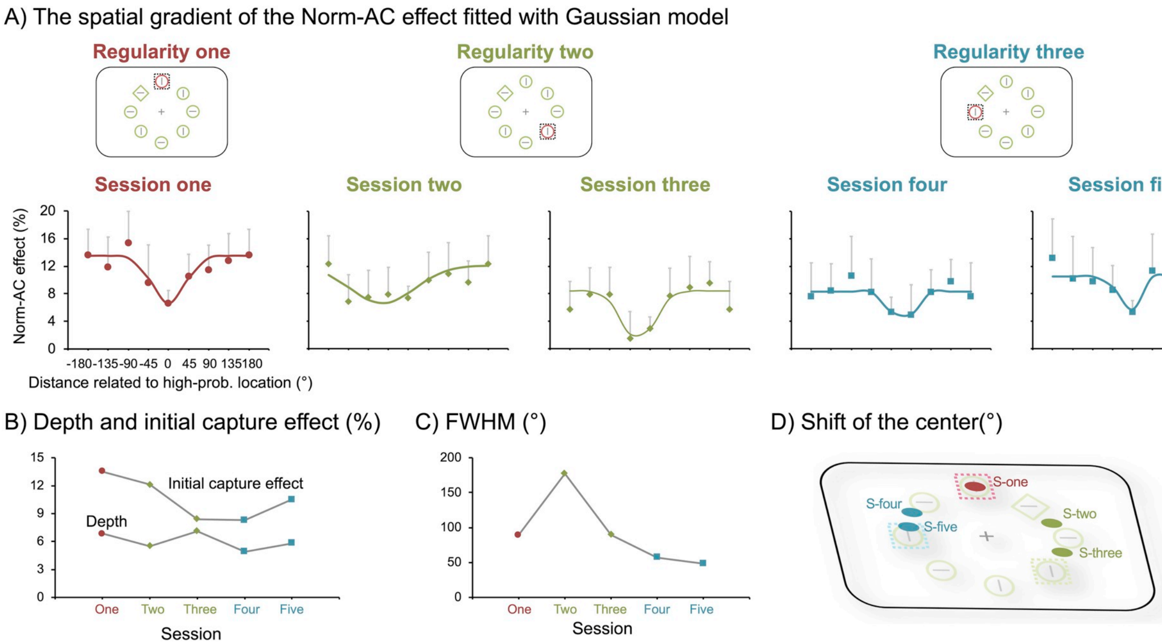

Fig. 5. A) The normalized attentional capture effects and their best fitting Gaussian curves for different sessions related to three different regularities. Regularities one, two, and three were marked by red, green, and blue, respectively. B) The depth of the gradient and the initial lingering bias (i.e., the initial attentional capture effect) for each regularity from the best-fitting Gaussian function. C) The FWHMs of the best-fitting Gaussian functions. D) The center of the spatial gradient from the best-fitting Gaussian function. The dashed outline squares indicated different high-probability locations of different regularities. The colored disks indicated different centers within different sessions. Error bars denote within-subjects 95% CIs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Best-fitting parameters for the suppression effects for different regularities and corresponding R^2.

Session	*D*	*c*	*w*	*b*	R^2
One (Regularity one)	6.9	0.1	89.4	13.5	0.84
Two (Regularity two)	5.5	−58.6	177.2	12.1	0.75
Three (Regularity two)	7.1	−26.4	89.7	8.4	0.81
Four (Regularity three)	4.9	24.1	57.3	8.3	0.83
Five (Regularity three)	5.8	−12.4	48.3	10.5	0.77

Note: *D* is the depth of the best-fitting Gaussian of the gradient of the suppression effect, *c* reflects the center of this gradient, and *w* is the full width at half maximum (FWHM), *b* represents the original lingering bias reflected by the attentional capture effect.

eight possible display-element locations, the distractor and target singleton only occurred along the horizontal and vertical axis (i.e., only occurred at four possible locations). The high-probability distractor location (which had a high probability of 46% containing a distractor; while other possible distractor locations had a low probability of 18% each) did not change to another location after one session, but it became the low-probability distractor location (which had a low probability of 4% containing a distractor, while other possible locations had a high probability of 32% each). Thus, at the end of the second session, the initial high- and low-probability locations had the same overall probability. Moreover, in the final session, the distractor was presented equally on every location. If the strong lingering bias observed in Experiment 1 was due to the overall probability explanation, the suppression effect should not have been found during the last session as during that session all overall probabilities were equal. After 40 practice trials, participants completed 3 sessions with each including 300 trials.

3.2. Results

Trials (2.8%) on which the response times (RTs) were larger or smaller than 2.5 standard deviations from the average response time per block per participant were excluded from analyses.

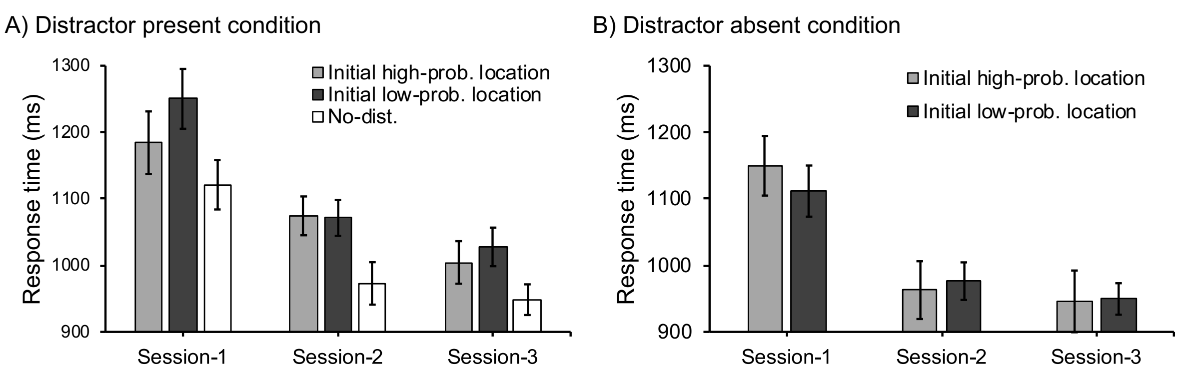

Fig. 6. The mean RTs between different distractor conditions for different sessions in distractor present condition (A) and distractor absent condition (B). Error bars denote within-subjects 95% CIs.

Mean RTs are presented in Fig. 6A. With *distractor location* (initial high-probability location, initial low-probability location, and no-distractor) and *session* (one, two, and three) as factors, a repeated ANOVA on mean RTs showed significant main effects for distractor location, $F(2, 46) = 47.66$, $p < .001$, partial $\eta^2 = 0.68$; and for session, $F(2, 46) = 37.41$, $p < .001$, partial $\eta^2 = 0.68$. Importantly, a significant interaction was observed, $F(4, 92) = 4.15$, $p = .004$, partial $\eta^2 = 0.15$. Compared to the no-distractor condition, the mean RTs were larger for initial high-probability location and low-probability location in all sessions, all $ps < .001$, suggesting that attention was captured by the salient distractors.

When comparing the difference between the initial high- and low-probability locations in the first session, the results showed that the mean RTs was smaller for initial high-probability location, $t(23) = 4.81$, $p < .001$ ($p = .002$ for unaware group[5]), suggesting a spatial suppression on the initial high-probability location. However, this suppression disappeared in the second session, $t < 1$ ($p = .484$ for unaware group); but seemed to reappear in the third session, $t(23) = 2.01$ $p = .056$ ($p = .058$ for unaware group). Together, the results indicate that, even when the overall probability was controlled by making the overall probability equal for each distractor location, in session 3, the original learned contingencies (from session 1) seemed to reappear suggesting that what was learned initially had a lingering effect. Moreover, the disappearance of the suppression effect in session 2 also reflects the flexible learning process, because the original learning (in session 1) was counteracted by the changing of the probability of frequent distractor location in session 2.

Mean RTs are presented in Fig. 6B. Repeated measures ANOVA on mean RTs with *distractor condition* (high- and low-probability locations) and *session* (one, two, and three) as factors showed main effects for session, $F(2, 46) = 41.2$, $p < .001$, partial $\eta^2 = 0.64$, but not for distractor condition, $F(1, 23) < 1$. The interaction was reliable, $F(2, 46) = 3.98$, $p = .03$, partial $\eta^2 = 0.15$. Following planned comparison showed that, only in the first session, there existed a suppression effect, $t(23) = 2.51$, $p = .02$; but did not exist in the following two sessions, both $ts < 1$.

Together, it suggests that the strong lingering biases observed in Experiment 1 was not due to an explanation in terms of a change in the overall probability.

4. General discussion

The present study shows that attentional selection is flexibly adapted to complex statistical regularities changing over time. People extract this information even though it contained regularities regarding the distractor which was never relevant for the task at hand. Consistent with previous findings (Ferrante et al., 2018; Wang & Theeuwes, 2018a, 2018b), we show reduced attentional capture by the distractor and target selection was less efficient when they are presented at the high- versus low-probability location. Moreover, the present study shows that these effects change with changing regularities in the display. It implies that people pick up on these changes quickly and adapt their behavior accordingly even though they were unaware of the changes introduced in the display. Critically, we show that people adapt to a changing environment but that there are lingering biases from previous learning experiences that impact the current selection priorities.

Our modelling pinpoints elegantly how people learn the changing contingencies regarding the distractor location. First, the evidence from the modelling analysis regarding normalized attentional capture effect shows that the initial attentional capture linearly decreases over sessions, suggesting that people continuously picked up the learning effects from previous regularities. This decrease of attentional capture across different sessions is the result of changing the high-probability location as this decrease is not observed when the location remains the same across sessions in Wang & Theeuwes, 2018a, 2018b (see Fig. 4A and B). Secondly, the initial high-probability location plays a more prominent role in biasing attentional selection than subsequent high-probability locations. Indeed, sessions two and three show a bias towards the initial (first) high-probability location. Crucially, session four also show a slight bias to initial high-probability location, even though immediately before session four participants experienced a different high-probability location (the one during sessions 2 and 3). Only during the final session, the center of the gradient is basically unbiased and directed exactly at the current high-probability location. Third, our modelling results show that the reduction of attentional capture effect was extended to all locations, and then its gradient becomes more focused around one location due to lingering biases.

Even though we show great flexibility in learning, we also show that the initial learning experience has the greatest lingering bias on subsequent learning. Indeed, the location that was most likely to contain a distractor during session one still had a measurable effect on the attentional bias in sessions two, three, and four. The role of initial learning was also evident in Experiment 2 in which what was learned in session one was to some extent reinstated in session three in which all locations were equally likely to contain a distractor. This lingering bias of the initial learned material is most likely due to proactive interference as reported in previous studies; yet, while these previous studies showed the greatest inflexibility to learn new associations (i.e., it took up to three days in the Zellin et al., 2014 for new learning to occur), in our task there was remarkable fast learning and flexible attentional selection.

Given previous studies that have shown little, if any, flexible adjustment to a changing environment, the current findings are intriguing given that here we show a quick adjustment that is adapted to a changing distractor probability distribution. The bottom-line is that when the distractor distribution changes, the attentional bias changes accordingly with a small lingering effect of initial learning (proactive interference). The question is then why the current study shows this great flexibility while previous studies, such as contextual cueing (Manginelli & Pollmann, 2009), context-target learning (Zellin et al., 2014), target location probability cueing (Jiang et al., 2013), and distractor location probability cueing (Sauter et al., 2019; Sauter, Liesefeld, Zehetleitner, & Müller, 2018), basically show persistent biases and no flexibility. There are many differences between these previous experiments and the current one which may explain why the outcomes of these studies are so different. One aspect that is crucial is that we employ the additional singleton task (Theeuwes, 1992) in which the distractor is so salient that it automatically captures attention. This implies that on most trials, attention is directed to the distractor location before it is shifted to the target location. This shift of attention to the distractor location is likely responsible for being able to quickly learn about the changing contingences of the high probability location of the distractor going from regularity one to two and from regularity two to three. Fast learning resulted in a fast and flexible updating of the weights of distribution of attention across the display. In other words, we argue that the change in the distractor distribution may be much more obvious because attention is automatically captured by the distractor location.

In many of the studies that show little flexibility there is not a salient singleton calling attention. Indeed, in most contextual cueing studies (e.g., searching Ts among Ls), nothing really stands out from the background. In that case attention is probably distributed evenly across the visual display. One might argue that there are other paradigms that also have shown little flexibility in unlearning and/or relearning even though a salient distractor was present in the display (e.g., Sauter et al., 2019, 2018). Note that in the current study there is *one* location containing a salient distractor that changes during the experiment. Even though this change was always probabilistic (the distractor appeared in

[5] Unware group (13 participants) was defined by participants that could not identify the high-probability location in sessions one and two.

65% at this one particular location) it was always about one location only. In studies that show little flexibility there was not a single contingency but instead participants had to learn and unlearn a large number of spatial arrangements (for example typical 12 arrangements in contextual cueing) and/or the distractor was presented within a global region in a display (for example the top half of a 32-item display in target and distractor location probability cueing). Because in previous studies there was much more variation in the display it may have prevented learning and unlearning. Finally, the current task was about learning regularities regarding the distractor location and not about the target or about target-distractor relationships. Since distractors and their locations are not part of the top-down task set, there may be little if any, blocking of new learning, resulting in highly flexible and adaptive selection. All these aspects may play a role; yet it is most likely that the automatic capture of attention by the salient singleton location plays the largest role in this fast learning.

Even though learning is fast and the capture of attention by the salient singleton may be evident, our awareness assessment indicated that most participants were not aware that the frequent distractor location changed. In addition, as our analysis indicates, if participants happened to have some awareness, this did not alter the results what so ever. If anything, this analysis suggests that for this type of learning to occur, awareness of the contingencies is not needed. Learning is most likely completely implicit. It should be noted however that the low awareness of the regularities may also be simply due to the fact that participants have forgotten the high-probability distractor location as it is known that there is little memory for task irrelevant features (Chen & Wyble, 2015).

In sum, the current findings suggest that through statistical learning the weights within the priority map are constantly adjusted such that the location that is high-likely to contain a distractor competes less for attention than all other locations. This process of adjusting the weights within the spatial priority map seems to be implicit, automatic, and highly adaptive (Chelazzi et al., 2014).

CRediT authorship contribution statement

Benchi Wang: Methodology, Data curation, Formal analysis, Writing - original draft, Writing - review & editing, Validation. **Jan Theeuwes:** Methodology, Writing - original draft, Writing - review & editing, Validation.

Declaration of competing interest

All authors approved the final version of the manuscript for submission, and they have no conflicts of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.actpsy.2020.103064.

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